# Hyperspectral Remote Sensing and Ecological Modeling Research and Education at Mid-America Remote sensing Center (MARC): Field and Laboratory Enhancement

Final Report to the NASA Grant No. NAG5-6582

by Haluk Cetin Principal Investigator

Mid-America Remote Sensing Center Murray State University Murray, KY 42071-0009

January 1999

Period Covered: 11/1/1997-10/31/1998

### TABLE OF CONTENTS

|    | Pa  | age |
|----|---|-----|
| ΑF | SSTRACT   | 1   |
| 1. | Introduction  | 2   |
| 2. | Education Accomplishments Using the Laboratory  | 4   |
| 3  | Research Accomplishments Using the Laboratory   | 4   |
| J. | 3.1. n-Dimensional Probability Density Functions (nPDF) and Intercrass  Distance Frequency Distribution (IDFD) techniques |     |
|    | 3.2. Mapping of water quality in Kentucky Lake using hyperspectral remote sensing   |     |
|    | 3.3. Spectral library   | 22  |
| 4. | Conclusions   | 26  |
| 5. | Acknowledgments   | 26  |
|    | Publications/Presentatitons during the project period   |     |

#### **ABSTRACT**

The purpose of this project was to establish a new hyperspectral remote sensing laboratory at the Mid-America Remote sensing Center (MARC), dedicated to in situ and laboratory measurements of environmental samples and to the manipulation, analysis, and storage of remotely sensed data for environmental monitoring and research in ecological modeling using hyperspectral remote sensing at MARC, one of three research facilities of the Center of Reservoir Research at Murray State University (MSU), a Kentucky Commonwealth Center of Excellence. The equipment purchased, a FieldSpec® FR portable spectroradiometer and peripherals, and ENVI hyperspectral data processing software, allowed MARC to provide hands-on experience, education, and training for the students of the Department of Geosciences in quantitative remote sensing using hyperspectral data, Geographic Information System (GIS), digital image processing (DIP), computer, geological and geophysical mapping; to provide field support to the researchers and students collecting in situ and laboratory measurements of environmental data; to create a spectral library of the cover types in Kentucky and other states; and to establish a World Wide Web server to provide the spectral library to other academic, state and Federal institutions. Much of the research will soon be published in scientific journals. A World Wide Web page (http://marc.mursuky.edu/projects/nasa97 98.htm) has been created at the web site of MARC. Results of this project are grouped in two categories, education and research accomplishments. The Principal Investigator (PI) modified remote sensing and DIP courses to introduce students to in situ field spectra and laboratory remote sensing studies for environmental monitoring in the region by using the new equipment in the courses. The PI collected in situ measurements using the spectroradiometer for the ER-2 mission to Puerto Rico project for the Moderate Resolution Imaging Spectrometer (MODIS) Airborne Simulator (MAS). Currently MARC is mapping water quality in Kentucky Lake and vegetation in the Land-Between-the Lakes (LBL) using Landsat-TM data. The PI and Dr. Naugle collected in situ spectra for the water quality research on May 31, 1998. A Landsat-TM scene of the same day was obtained to relate ground measurements to the satellite data. A spectral library has been created for overstory species in LBL. Some of the methods, such as nPDF and IDFD techniques for spectral unmixing and reduction of effects of shadows in classifications; comparison of hyperspectral classification techniques; and spectral nonlinear and linear unmixing techniques, are being tested using the laboratory.

#### 1. Introduction

This report presents the research and education accomplishments for the NASA Project NAG5-6582 "Hyperspectral Remote Sensing and Ecological Modeling Research & Education at Mid-America Remote sensing Center (MARC): Field and Laboratory Enhancement" at MARC, Murray State University (MSU), Murray, Kentucky from November 1997 through October 1998. Two assistants at MARC have worked with the Principal Investigator (PI) to accomplish the tasks involved.

The purpose of this project was to establish a new hyperspectral remote sensing laboratory at MARC, dedicated to in situ and laboratory measurements of environmental samples and to the manipulation, analysis, and storage of remotely sensed data for environmental monitoring and research in ecological modeling using hyperspectral remote sensing at MARC, one of three research facilities of the Center of Reservoir Research at MSU, a Kentucky Commonwealth Center of Excellence. The equipment purchased, a FieldSpec® FR portable spectroradiometer and peripherals, and ENVI hyperspectral data processing software, allowed MARC: 1) to provide hands-on experience, education, and training for the students of the Department of Geosciences in quantitative remote sensing using hyperspectral data, Geographic Information System (GIS), Digital Image Processing (DIP), computer, geological and geophysical mapping; 2) to provide field support to the researchers and students collecting in situ and laboratory measurements of environmental data; 3) to give more stimulating and improved learning experience through modern educational technology to students enrolled in the Geosciences; 4) to create a spectral library of the cover types in Kentucky and other states; 5) to establish a World Wide Web server to provide the spectral library to other academic, state and Federal institutions; 6) to support undergraduate and graduate curricula in remote sensing and GIS in the Department; and 7) to encourage use of remote sensing in environmental research and monitoring. The PI modified remote sensing, and DIP courses to introduce students to in situ field spectra and laboratory remote sensing studies for environmental monitoring in the region. The new equipment has been used in the Geoscience courses in remote sensing/DIP. The students in the Department are becoming more competitive in the field of hyperspectral remote sensing. One of the PI's graduate students who has been working on a project involving hyperspectral measurements using the spectroradiometer to study effects of toxic metals on vegetation has already started working for a high-tech company at the Stennis Space Center. Another graduate student of the PI is conducting

a research on the effects of petroleum on vegetation spectra. The PI has been able to collect *in situ* measurements using the spectroradiometer for the ER-2 mission to Puerto Rico project for the Moderate Resolution Imaging Spectrometer (MODIS) Airborne Simulator (MAS). Currently MARC is mapping water quality in Kentucky Lake and vegetation in the Land-Between-the Lakes (LBL) using Landsat-TM data. Drs Naugle and Cetin collected *in situ* spectra for the water quality research on May 31, 1998. A Landsat-TM scene of the same day was obtained to relate ground measurements to the satellite data. A spectral library has been created for overstory species in LBL. MARC is in the process of enhancing reservoir hydrologic, sedimentologic, and biologic modeling. Particularly the field spectroradiometer has been a vital part of this project to obtain field data to support ecological modeling research and education at MARC and the Department of Geosciences at Murray State University. The laboratory will impact both researchers at MARC, and majors in Geosciences and non-majors with regard to modern technologies associated with the rapidly growing fields of remote sensing, GIS, DIP, and computer mapping.

Results of the project are grouped in two categories, education and research. Education accomplishments using the laboratory described in this report are: 1) modification of remote sensing related courses to include hyperspectral remote sensing; and 2) hands-on experience, education, and training for the students of the Department of Geosciences in quantitative remote sensing using hyperspectral data.

Research in four major areas using the laboratory is described in this report:

1) classification algorithm development using the n-Dimensional Probability Density
Functions (nPDF) and Interclass Distance Frequency Distribution (IDFD) techniques
for reduction of effects of shadows in classifications and linear and non-linear spectral
mixture studies; 2) mapping of water quality in Kentucky Lake using hyperspectral
remote sensing; and 3) field spectra collection for remotely sensing studies and
construction of spectral library for western Puerto Rico and western Kentucky.

A World Wide Web page (http://marc.mursuky.edu/projects/nasa97\_98.htm) has been created for this research at the web site of MARC. More detailed and up-to-date research is available at the web site. The spectral libraries at the home page are available in ASCII and graphics formats.

## 2. Education Accomplishments Using the Laboratory

The PI has modified his Advanced Remote Sensing and DIP courses to include hyperspectral remote sensing and to provide hands-on experience, education, and training for the students of the Department of Geosciences in quantitative remote sensing using hyperspectral data.

New laboratory exercises have been created using the ENVI software and the equipment. Students analyzed samples and obtained reflectance spectra of the samples to include in processing of hyperspectral data, such as AVIRIS data of Cuprite, Nevada. Some of the students of the courses used the spectroradiometer for their term projects. Environmental data have been and will be collected to be used by the students and researchers for ecological modeling research.

The PI has been working on a manual for students and researchers to use the laboratory equipment. All the necessary processing and warnings regarding the measurements of reflectance and absorption/transmission spectra are included in the manual.

The students in the Department are becoming more competitive in the field of hyperspectral remote sensing. One of the PI's graduate students who has been working on a project involving hyperspectral measurements using the spectroradiometer to study effects of toxic metals on vegetation has already started working for a high-tech company at the Stennis Space Center. Another graduate student of the PI will be conducting a research on the effects of petroleum on vegetation spectra.

# 3. Research Accomplishments Using the Laboratory

Research in four major areas using the laboratory is described in this report: 1) classification algorithm development using the n-Dimensional Probability Density Functions (nPDF) and Interclass Distance Frequency Distribution (IDFD) techniques for reduction of effects of shadows in classifications and linear and non-linear spectral mixture studies; 2) mapping of water quality in Kentucky Lake using hyperspectral remote sensing; and 3) field spectra collection for remotely sensing studies and construction of spectral library for western Puerto Rico and western Kentucky.

# 3.1. n-Dimensional Probability Density Functions (nPDF) and Interclass Distance Frequency Distribution (IDFD) techniques

The nPDF procedure is an approach to the display, analysis, reduction and classification of multispectral data. In this research, the applications of the nPDF classification of remotely sensed data with shadow problems are illustrated. The IDFD technique is being developed further to improve classification of mixtures and data with shadow problems.

Classification algorithms may be divided into two broad categories, parametric and nonparametric classifications. Parametric or relative classification algorithms generally assume normal statistical distribution for classes. Parametric classifiers, such as maximum likelihood and Mahalanobis distance, require selection of training fields representing the entire area classified. When there are large number of classes, a relative classifier is usually preferred. On the other hand, nonparametric or absolute techniques do not assume any particular class statistical distribution. When an absolute classification, such as parallelelepiped classification scheme, is used, only classes of interest are classified.

Previous studies on the classification of remotely sensed data have shown the difficulties of selecting a classification method. The commonly used relative classification techniques, such as maximum likelihood and Mahalanobis distance, have limited capability for a special purpose classification. When the relative classifiers are used, interclass distances can be shown only statistically. For special purpose classifications, absolute classification schemes have more advantageous than relative classifiers. One of the approaches for an absolute classification of multispectral data is n-Dimensional Probability Density Functions (nPDF) procedure.

Previous studies on the display, analysis, and classification of remotely sensed data have shown the difficulties of selecting a classification method. The commonly used classification techniques, such as maximum likelihood and Mahalanobis, have a number of inherent limitations. These limitations include: 1) The memory requirements of the computer routines tend to be very large for high dimensional data, and the run-times are very long. Therefore, the algorithms tend to be implemented in computer routines that allow for only a limited number of input bands. 2) The algorithms are relative classifiers, and thus training fields from all spectral classes need to be identified prior to classification. Classes are described statistically; therefore it is very difficult to check if the training fields selected represent the entire data. 3) Class overlap, class distribution and interclass

distances can be shown for only two bands at a time. Furthermore, interclass distances can be shown only statistically. 4) The algorithms assume the data are normally distributed, although this is rarely the case.

The nPDF procedure, a nonparametric classification technique, is an approach to the display, analysis, reduction and classification of multispectral data that overcomes many of the problems described above. The nPDF approach may be explained using a cube model. In three dimensional feature space the feature vector is defined by  $X=[x_1,x_2,x_3]$ . The location of the measurement within the range of the total possible measurement space can be described by the distances to the two corners of a cube:

$$D_1 = (x_1^2 + x_2^2 + x_3^2)^{1/2}$$
, and  $D_2 = [x_1^2 + x_2^2 + (R - x_3)^2]^{1/2}$ 

For the multi-dimensional case, the feature vector is defined by  $X=[x_1,x_2,x_3,...,x_n]$ , where n is the dimension of the data and R is the maximum possible range of the data (255 for 8 bit data.) When a hyper-dimensional cube is used, the vector magnitudes (the distances to the two corners) for n- dimensional data are:

$$D_{1} = \left(\sum_{j=1}^{n} x_{j}^{2}\right)^{1/2}$$

$$D_{2} = \left(\sum_{j=1}^{n} x_{j}^{2} * (1 - a_{j}) + (R - x_{j})^{2} * a_{j}\right)^{1/2}$$
if  $\begin{cases} j = 1, 2, 4, 5, \dots & a = 0 \\ j = 3, 6, \dots & a = 1 \end{cases}$ 

where j is the band number. A generalized formula for the distance to the corners of a hyper-dimensional cube can be written as (i is the corner or component number):

$$D_{i} = \left(\sum_{j=1}^{n} x_{j}^{2} * (1 - a_{j}) + (R - x_{j})^{2} * a_{j}\right)^{1/2}$$
 (1)

There are eight possible corners of a three-dimensional cube (Figure 1). Four of the corners can be selected as principal corners (1 through 4), the remaining corners (5 through 8) are the complimentary to the four principal corners. For the hyper-dimensional cube model, "a" values for the equation (1) are as follows (j is the band number):

The nPDF formula is:

$$nPDF_i = S * D_i / (2^{BIT} * NB^{1/2})$$
 (2)

where,

 $nPDF_i = Component i of nPDF,$ 

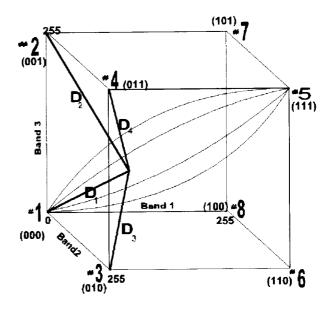
i = Corner number,

S = Desired scale for the nPDF axes,

BIT = Number of bits of input data,

NB = Number of bands used.

D<sub>i</sub> = Calculated distance for component i,



Frequency plots of two nPDF components (hyper-dimensional distances) provide an excellent perspective of multidimensional data distribution. Ignoring complimentary corners, there are six possible combinations of two corners from which to view the data distribution (1-2, 1-3, 1-4, 2-3, 2-4, and 3-4.) Depending on the spectral distribution of the classes of interest, the user can select corners, which provide the maximum separation of the classes. A convenient scale for these nPDF components is 8 bit in range, and thus a 2-dimensional frequency plot requires a 256 by 256 array.

The cube model has the advantage of being a conceptually simple way of describing corners in multidimensional space. However, it does tend to limit the choice of corners for four and higher dimensional data. Where this is a problem, we use the "a" values (see equation 1) to describe the corner location. Thus, corner #2 is also labeled (001), which can be interpreted as a corner that is the minimum for the first two bands, and the maximum in the third band. Using this convention, the length of the list of "a" values

depends on the number of input bands, and thus the corner corresponding to the origin in a four band image would be described as (0000).

The Interclass Distance Frequency Distribution (IDFD) technique is an absolute classification approach for multispectral data classification. The IDFD displays data and class distribution graphically. The IDFD approach is user-interactive and can be used for sub-pixel classification.

The IDFD technique can be explained by using two class example. In feature space the distances to class means can be generalized as

$$d_{ik} = |M_k - X_i|$$

where

d = distance between a feature and a defined class

j = feature (pixel)

k = class

X = feature vector

 $M_k$  = mean vector of class k

Initially two classes of interest are selected and their statistical information is obtained by using training fields. The mean measurement vectors of the classes are used to calculate the distances for each pixel of the data and stored in a two dimensional frequency data array. The following IDFD formula is utilized to calculate the two-dimensional data distribution by using a desired scale factor and the known parameters of the data:

$$IDFD_{jk} = d_{jk} * S / (n^{1/2} * A)$$

where

 $IDFD_{ik} = IDFD$  value of the feature (pixel) for class k

S = scale for the axes

n = number of bands (dimensions) used

A = maximum range of the data

One of the ways to perform the IDFD classification is to use two classes as reference points. In two-dimensional feature space, each data axis represents the distance to the

reference class. Training fields are selected for other classes and the training data distribution (frequencies) using the distances to the reference classes is obtained. After examining the results visually, a classification look-up table is created and the classification is performed by using the look-up table.

The magnitude of the distances can be calculated by using one of the distance measures, such as Euclidean distance. The use of other distance measures utilizing covariance matrix along with mean measurement vector can be an advantage and may improve the classification results by improving the class separation.

For this research, nPDF technique was used to determine if the technique could improve the classification of areas with shadow problems. In order to do examine the problem, a land cover type, Tertiary sand sample, was used to determine the spectral reflectance characteristics of the samples under different shadow conditions. Three levels, 100% reflectance (no shadow), 50% and 25% shadow conditions were used to test the nPDF technique. The nPDF1 and nPDF4 values were calculated and plotted in the nPDF space (Figure 2).

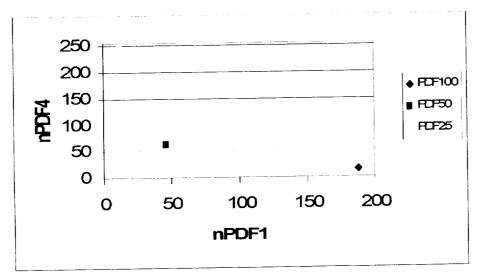


Figure 2. nPDF data distribution: 100% (PDF100), 50% (PDF50), and 25% (PDF25) light conditions

A series of statistical analyses (trend analysis: logarithmic, exponential, polynomial and power) were attempted to find the best fit. The power trend analysis had the best fit  $(y = 2994.7 \text{ s}^{-1})$  with a  $R^2$  value of 0.999 (Figure 3).

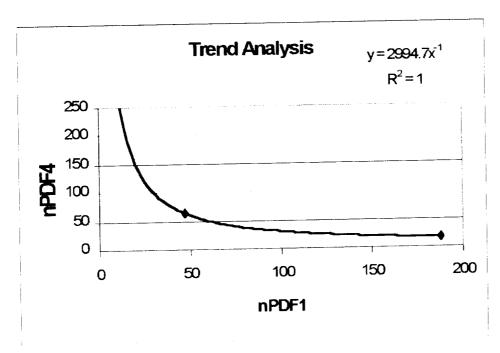


Figure 3. Trend analysis of the nPDF data distribution

This test shows that the nPDF values can be used to determine land cover types in shadows. Other sets of tests are planned to examine and validate the findings of this research. The technique is also being tested for spectral unmixing.

Some of the methods that are being tested using the laboratory are as follows: Testing of the IDFD technique for spectral unmixing and reduction of effects of shadows in classifications; testing and comparison of hyperspectral classification techniques; testing of some hypotheses related to spectral nonlinear and linear unmixing techniques by using some systematic tests being conducted on mixtures of minerals, vegetation/soil, and some surface materials. Initial findings showed that at mm/cm level, linear mixing techniques did not work. Please visit our home page at <a href="http://marc.mursuky.edu/projects/nasa97\_98.htm">http://marc.mursuky.edu/projects/nasa97\_98.htm</a> for additional and up-to-date information.

# 3.2. Mapping of water quality in Kentucky Lake using hyperspectral remote sensing

Methods currently used to monitor water quality across the landscape consist of *in situ* measurements or collection of water samples for analysis in a laboratory. These

techniques are time consuming and expensive, and do not give the synoptic and temporal views of a landscape necessary to allow management decisions that can effectively control or improve water quality. Major factors affecting water quality are suspended sediment, chlorophyll, dissolved organic matter (DOM), and chemicals derived from natural sources and human activities. Suspended sediment, chlorophyll, and DOM cause changes in the optical characteristics of surface waters. The potential therefore exists for monitoring these parameters by measuring the optical characteristics of surface waters with remote sensing techniques.

The objective of this study was to use Landsat-TM and field spectroradiometer data to map turbidity levels in the Blood river Embayment of Kentucky Lake. The relation between Landsat TM radiance values and ground spectra values for all four bands, and measured values of suspended sediment concentrations and turbidity were quantified using simple linear and multiple regression equations. An optimum/best fitted equation was chosen. This calibrated regression model was then applied to map the suspended sediment concentrations and turbidity for the entire study area. It is shown that Landsat-TM data can be used successively to quantify suspended sediment concentrations in the Blood river embayment.

An attempt has been made to develop a monitoring procedure to correlate the spectral reflectance data obtained using the field spectroradiometer and Landsat TM data. Samples and ground spectra were collected on 31 May 1998 concurrent with satellite overpass at 10 sites located in the Blood river embayment of Kentucky Lake (Figure 4). Trimble GPS was used for precise location of sampling points.

Water Quality Parameters like, suspended sediment, chlorophyll, vertical extinction coefficient, Dissolved oxygen & pH were analyzed for the sites. The field spectroradiometer was used to measure spectra from 350 - 2500 nm at the locations on 31 May 1998 (Figures 5 thru 14).

Satellite image values and ground reflectance values were correlated to the values derived from water samples collected during the overflight of the Landsat TM. The satellite image values and the water parameter values were used as input to a regression analysis. The relationships generated using the regression analysis were used to transform the satellite reflectance data into the water parameters of interest. Average embayment turbidity estimates were calculated using satellite-derived values. A model was created using a georeferenced satellite image of 05/31/1998 and water quality parameters obtained

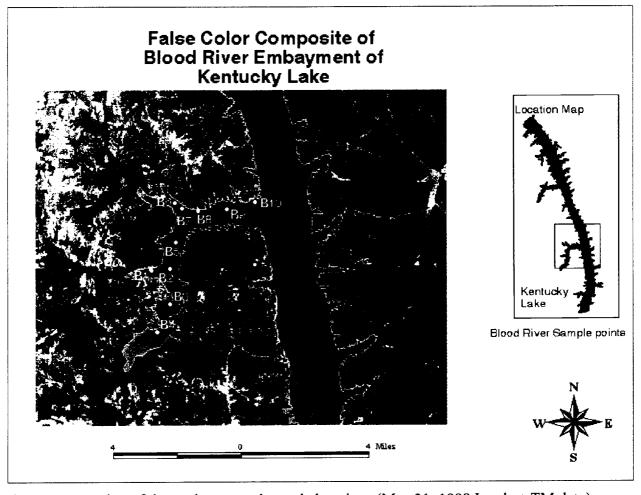


Figure 4. Location of the study area and sample locations (May 31, 1998 Landsat-TM data)

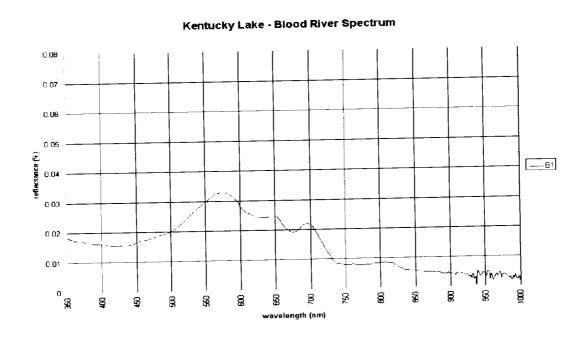


Figure 5. Spectral reflectance curve of station B1 (May 31, 1998)

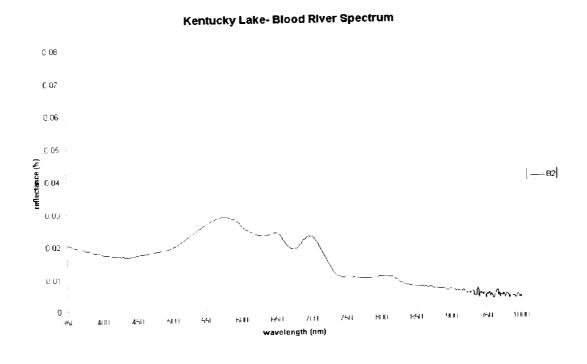


Figure 6. Spectral reflectance curve of station B2 (May 31, 1998)

### Kentucky Lake - Blood River Spectrum

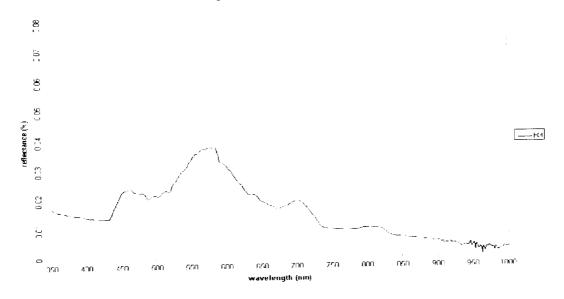


Figure 7. Spectral reflectance curve of station B3 (May 31, 1998)

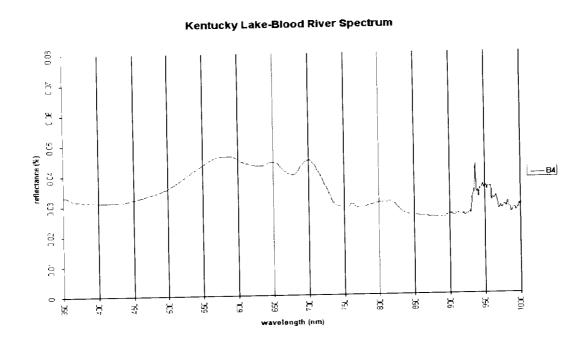


Figure 8. Spectral reflectance curve of station B4 (May 31, 1998)

#### KENTUCKY LAKE -BLOODRIVER SPECTRUM

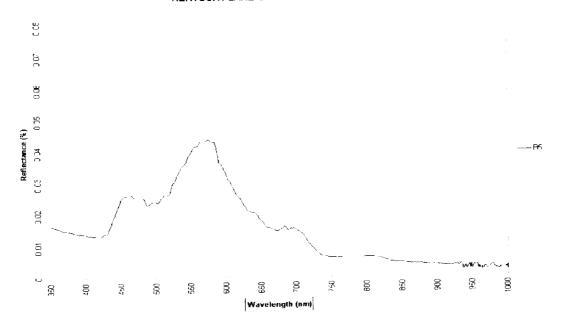


Figure 9. Spectral reflectance curve of station B5 (May 31, 1998)

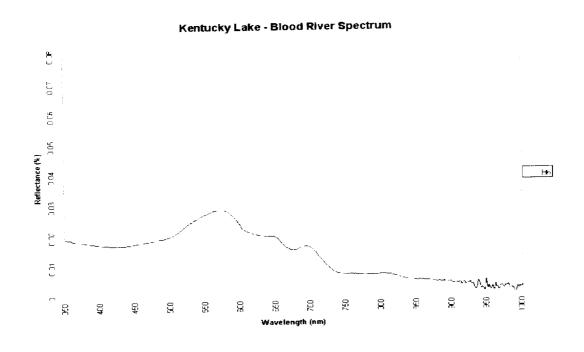


Figure 10. Spectral reflectance curve of station B6 (May 31, 1998)

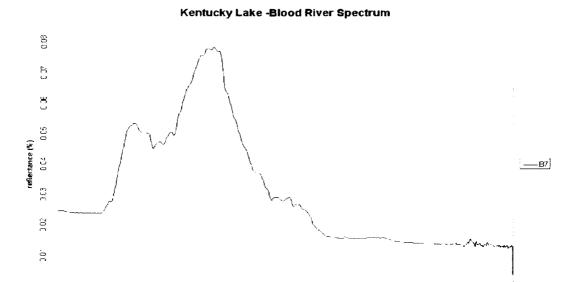


Figure 11. Spectral reflectance curve of station (May 31, 1998)

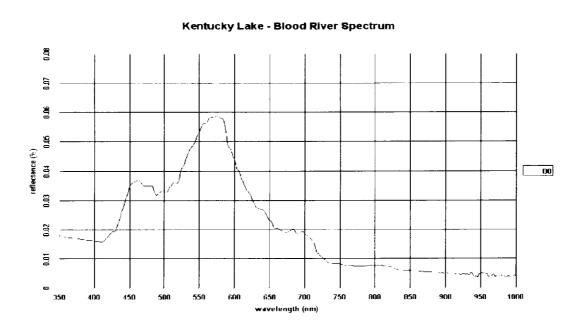


Figure 12. Spectral reflectance curve of station B8 (May 31, 1998)

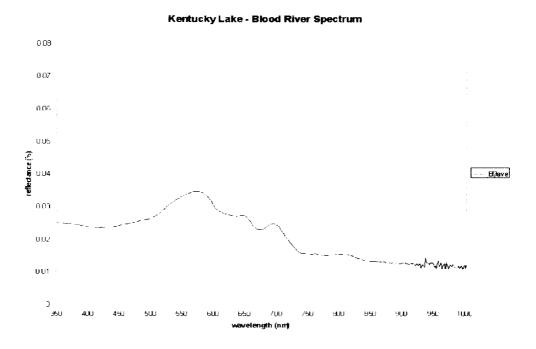


Figure 13. Spectral reflectance curve of station B9 (May 31, 1998)

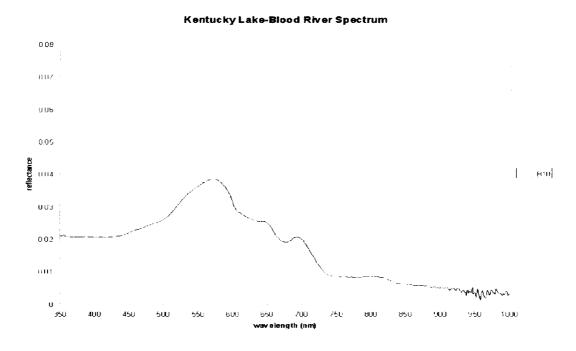


Figure 14. Spectral reflectance curve of station (May 31, 1998)

through Hancock Biological Station. Relationships between satellite and concurrent turbidity (Figure 15) field data were examined through a regression analysis. In the

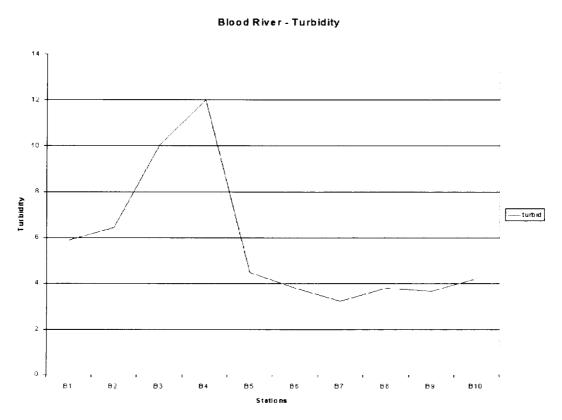


Figure 15. Blood River turbidity levels

selection process, the Landsat TM bands and the ground spectra corresponding to the four bands (of the TM bands 1, 2, 3, and 4), and water quality parameters were considered (Figures 16 and 17).

#### **SPECTRA CORRELATION**

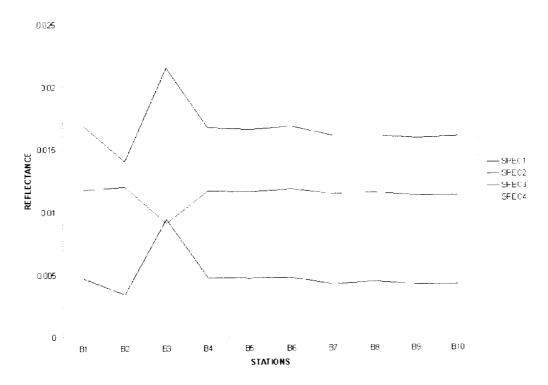


Figure 16. Correlation of the four band values (obtained from the spectroradiometer data) of the stations

The reflectance of water and increasing suspended sediment concentrations had a positive correlation. Mapping suspended sediment concentrations and chlorophyll using satellite images provided mixed results. In general, chlorophyll concentrations were inversely related to suspended sediment concentrations. Reflectance calculated from the four Landsat TM bands increased as a function of increasing concentrations of suspended sediment. The reflectance values were inversely related to the concentration of chlorophyll but the relationships were not statistically significant. A series of statistical models were developed and examined to determine the best relationship between the measurements of suspended sediment concentrations at the 10 sample locations and the reflectance values computed from all four bands of the Landsat-TM (Figure 17) and the spectrometer reflectance values. Based on the R<sup>2</sup> and the simplicity models, the best

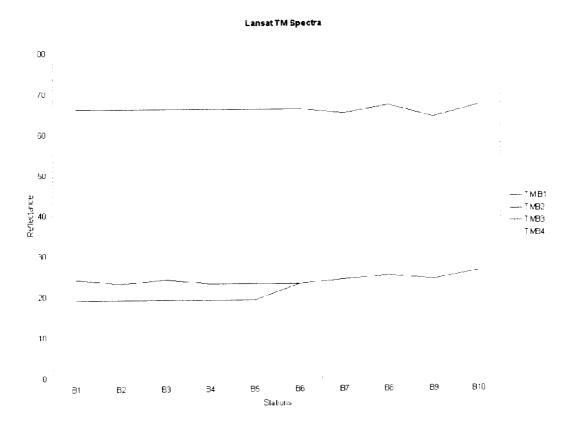


Figure 17. Correlation of the four TM band values

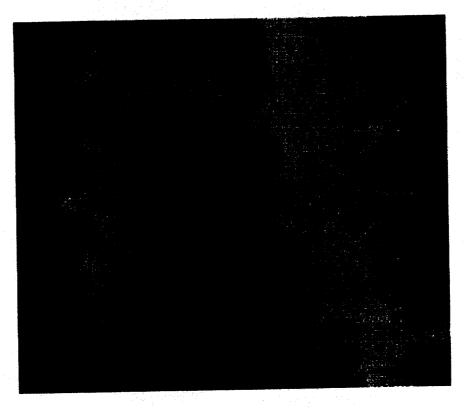
appropriate model was determined through multiple regression technique using SAS software. The following equations were selected to represent the best relation between the suspended sediment/turbidity concentrations and their corresponding radiance values of the Landsat TM data (Figure 18).

Suspended Sediment = 64.8929 - 2.4174 TMBand3

Turbidity = 23.9026 - 0.8189 TMBand3

The  $R^2$  determination is 0.6046 for suspended sediment and 0.5960 for turbidity. The calibrated regression model was extended to the study area for mapping of suspended

# Bloodriver embayment of Kentucky lake showing Turbidity levels.



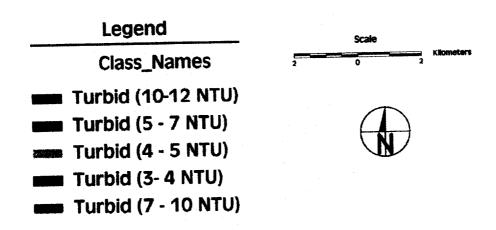


Figure 18. Turbidity levels of the study area

sediment concentrations and turbidity. The extension of this model was done by using a simple linear discriminant function (Imagine Map Modeler Software). By applying the function to each pixel in the study area and then grouping the water quality variability into

classes. Field spectroradiometer reflectance values were imported in to Excel to analyze the corresponding the four bands of the TM data.

Calibrated regression models that relate remotely sensed data to field measurements may be used to provide maps of the synoptic distributions of water quality maps. The present study used the TM data in conjunction with the FieldSpec spectroradiometer reflectance values with their corresponding physical values for mapping of suspended sediment concentrations and turbidity in Blood river Embayment of Kentucky Lake. In order to quantitatively determine suspended sediment concentrations, high spectral resolution at approximately 675 and 705 nm is required.

#### 3.3. Spectral library

A spectral library dedicated to *in situ* and laboratory measurements of environmental samples for environmental monitoring and research in ecological modeling has been created at the web site of MARC. Spectra of various cover types in Kentucky and other states are being added to the spectral library and are available at the web site (http://marc.mursuky.edu/projects/nasa97\_98.htm). The PI has been mapping overstory vegetation (Table 1) in the Land-Between-the Lakes (LBL) using Landsat-TM data. Reflectance spectra of most of the overstory species (Table 1) in LBL are available at the web site (Figure 19).

The PI collected *in situ* measurements using the spectroradiometer for the ER-2 mission to Puerto Rico project for the Moderate Resolution Imaging Spectrometer (MODIS) Airborne Simulator (MAS). In order to make atmospheric corrections and reflectance conversions, field spectral measurements at sites with considerable size are needed. Two of the measurements (Figures 20 and 21) were taken at the two airports, Ramey and Mayaguez, since these airports are the largest available targets to correct the MAS data. The other spectral measurements will be processed and added to the spectral library. The PI is currently compiling all the data with ground pictures. These data will also be available at the web site.

Table 1. Overstory Vegetation Species in LBL

| <u>acronym</u> | genus        | <u>species</u> | authority           | common name        | habit     |
|----------------|--------------|----------------|---------------------|--------------------|-----------|
| ACNE           | Acer         | negundo        | L.                  | boxelder           | overstory |
| ACRU           | Acer         | rubrum         | L.                  | red maple          | overstory |
| ACSA           | Acer         | saccharum      | Marsh.              | sugar maple        | overstory |
| BENI           | Betula       | nigra          | L                   | river birch        | overstory |
| CACO           | Carya        | cordiformis    | (Wangenh.) K.       | bitternut hickory  | overstory |
| CAGL           | Carya        | glabra         | (Miller) Sweet      | pignut hickory     | overstory |
| CAIL           | Carya        | illinoensis    | Wang                | pecan              | overstory |
| CALA           | Carya        | laciniosa      | (Michaux f.) Loudon | shellbark hickory  | overstory |
| CAOVT          | Carya        | ovata          | Miller              | shagbark hickory   | overstory |
| CAOVL          | Carya        | ovalis         | (Wangenh.) Sarg.    | red hickory        | overstory |
| CATO           | Carya        | tomentosa      | (Poiret) Nutt.      | mockernut hickory  | overstory |
| CELA           | Celtis       | laevigata      | Willd.              | sugarberry         | overstory |
| CEOC           | Celtis       | occidentalis   | L.                  | hackberry          | overstory |
| CLKE           | Cladrastis   | kentukea       | (DumCours.) Rudd    | yellowwood         | overstory |
| DIVI           | Diospyros    | virginiana     | L.                  | persimmon          | overstory |
| FAGR           | Fagus        | grandifolia    | Ehrh.               | american beech     | overstory |
| FRAM           | Fraxinus     | americana      | L.                  | white ash          | overstory |
| FRPE           | Fraxinus     | pennsylvanica  | Marshall            | green ash          | overstory |
| GLTR           | Gleditsia    | triacanthos    | L.                  | honeylocust        | overstory |
| JUCI           | Jugians      | cinerea        | L.                  | butternut          | overstory |
| JUNI           | Juglans      | nigra          | L.                  | black walnut       | overstory |
| LIST           | Liquidambar  | styraciflua    | L.                  | sweetgum           | overstory |
| LITU           | Liriodendron | tulipifera     | L.                  | yellow poplar      | overstory |
| MORU           | Morus        | rubra          | L.                  | red mulberry       | overstory |
| NYSY           | Nyssa        | sylvatica      | Marshall            | blackgum           | overstory |
| OXAR           | Oxydendrum   | arboreum       | (L.) DC.            | sourwood           | overstory |
| PIEC           | Pinus        | echinata       | Miller              | shortleaf pine     | overstory |
| PIST           | Pinus        | strobus        | L.                  | eastern white pine | overstory |
| PITA           | Pinus        | taeda          | L.                  | lobiolly pine      | overstory |
| PIVI           | Pinus        | virginiana     | Miller              | virginia pine      | overstory |
| PLOC           | Platanus     | occidentalis   | L.                  | sycamore           | overstory |
| PODE           | Populus      | deltoides      | Bartram ex Marshall | eastern cottonwood | overstory |
| POHE           | Populus      | heterophylla   | L.                  | swamp cottonwood   | overstory |
| PRSE           | Prunus       | serotina       | Ehrh.               | black cherry       | overstory |
| QUAL           | Quercus      | alba           | L.                  | white oak          | overstory |
| QUBI           | Quercus      | bicolor        | Willd.              | swamp White Oak    | overstory |
| QUCO           | Quercus      | coccinea       | Muenchh.            | scarlet oak        | overstory |
| QUFA           | Quercus      | falcata        | Michaux             | southern red oak   | overstory |
| QUIM           | Quercus      | imbricaria     | Michx.              | shingle Oak        | overstory |
| QULY           | Quercus      | lyrata         | Walter              | overcup oak        | overstory |
| QUMA           | Quercus      | marilandica    | Muenchh.            | blackjack oak      | overstory |
| QUMC           | Quercus      | macrocarpa     | Michx.              | bur Oak            | overstory |
| QUMI           | Quercus      | michauxii      | Nutt.               | swamp chestnut oak | overstory |

Table 1 (Cont.). Overstory Vegetation Species in LBL

| acronym | genus     | species       | authority    | common name        | <u>habit</u> |
|---------|-----------|---------------|--------------|--------------------|--------------|
| QUMU    | Quercus   | muehlenbergii | Engelm.      | chinquapin oak     | overstory    |
| QUNI    | Quercus   | nigra         | L.           | water oak          | overstory    |
| QUPA    | Quercus   | pagoda        | Raf.         | cherrybark oak     | overstory    |
| QUPH    | Quercus   | phellos       | L.           | willow oak         | overstory    |
| QUPL    | Quercus   | palustris     | Muench.      | pin oak            | overstory    |
| QUPR    | Quercus   | prinus        | 1            | chestnut oak       | overstory    |
|         | Quercus   | rubra         | 1            | northern red oak   | overstory    |
| QURU    |           | shumardii     | Buckley      | shumard oak        | overstory    |
| QUSH    | Quercus   | stellata      | Wangenh.     | post oak           | overstory    |
| QUST    | Quercus   | velutina      | Lam.         | black oak          | overstory    |
| QUVE    | Quercus   | caroliniana   | Walter       | carolina buckthorn | overstory    |
| RHCA    | Rhamnus   |               | I            | black locust       | overstory    |
| ROPS    | Robinia   | psuedoacacia  | (Nutt.) Nees | sassafras          | overstory    |
| SAAL    | Sassafras | albidum       | <del></del>  | black willow       | overstory    |
| SANI    | Salix     | nigra         | Marshall     | bald cypress       | overstory    |
| TADI    | Taxodium  | distichum     | (L.) Rich.   |                    | overstory    |
| ULAL    | Ulmus     | alata         | Michaux      | winged elm         |              |
| ULAM    | Ulmus     | americana     | L.           | american elm       | overstory    |
| ULRU    | Ulmus     | rubra         | Muhlenb.     | slippery elm       | overstory    |

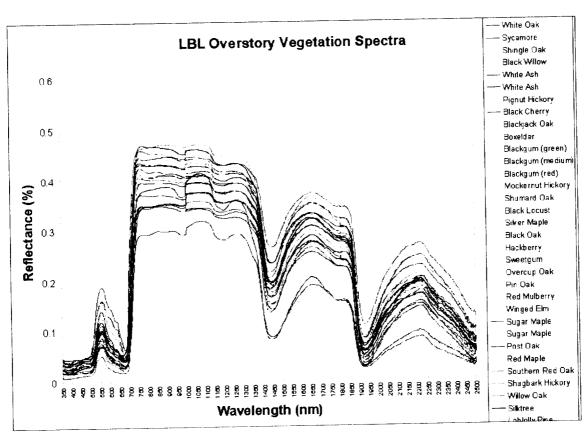


Figure 19. Spectral reflectance curves of overstory vegetation species in LBL

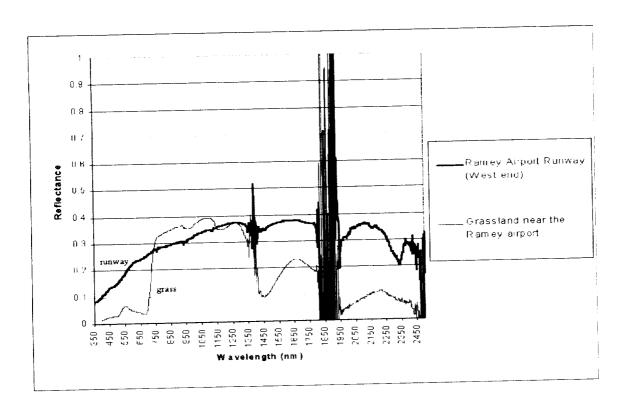


Figure 20. Spectral reflectance curves of Ramey Airport in northwestern Puerto Rico

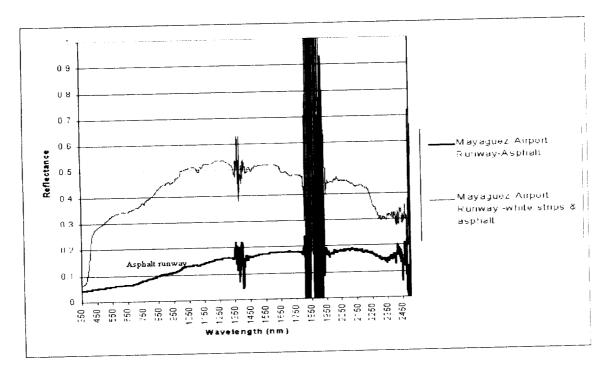


Figure 21. Spectral reflectance curves of Mayaguez airport in western Puerto Rico

#### 4. Conclusions

The purpose of this project was to establish a new hyperspectral remote sensing laboratory at MARC dedicated to *in situ* and laboratory measurements of environmental samples. The equipment purchased, a FieldSpec® FR portable spectroradiometer and peripherals, and ENVI hyperspectral data processing software, allowed MARC to provide hands-on experience, education, and training for the students of the Department of Geosciences in quantitative remote sensing using hyperspectral data. A World Wide Web server was created to provide the spectral library to other academic, state and Federal institutions. Much of the research will soon be published in scientific journals. Some of the methods, such as nPDF and IDFD techniques for spectral unmixing and reduction of effects of shadows in classifications; comparison of hyperspectral classification techniques; and spectral nonlinear and linear unmixing techniques, are being tested using the laboratory.

#### 5. Acknowledgments

The PI wishes to thank Dr. Armond Joyce of the Stennis Space Center and Jeff Myers of Ames Center of NASA for providing the MAS data. This study was supported by the NASA, Grant No. NAG5-6582.

### 6. Publications/Presentatitons during the project period

Cetin, H. and A. Wong 1998. Land Cover Mapping of Western Puerto Rico using MODIS Airborne Simulator (MAS) data. ASPRS/RTI Conference: Tampa, Florida, 83-91.